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Review

# Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility

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## HIGHLIGHTS

- Overview of battery aging process, measured variables and aging factors.
- Presenting general Battery SoC estimation and SoH prediction techniques.
- Review data-driven and physical-model PHM approaches.
- Evaluate PHM techniques in battery safety.

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## ABSTRACT

As hybrid and electric vehicle technologies continue to advance, car manufacturers have begun to employ lithium ion batteries as the electrical energy storage device of choice for use in existing and future vehicles. However, to ensure batteries are reliable, efficient, and capable of delivering power and energy when required, an accurate determination of battery performance, health, and life prediction is necessary. This paper provides a review of battery prognostics and health management (PHM) techniques, with a focus on major unmet needs in this area for battery manufacturers, car designers, and electric vehicle drivers. A number of approaches are presented that have been developed to monitor battery health status and performance, as well as the evolution of prognostics modeling methods. The goal of this review is to render feasible and cost effective solutions for dealing with battery life issues under dynamic operating conditions.



## 1. Introduction

The growth of the electric vehicle market is dependent on driving range, reliability, safety and power management systems. Batteries have been used widely in both electric vehicles (EV) and hybrid electric vehicles (HEV) due to their simple functional characteristics and affordable expenses within electric driving mode [1]. The rechargeable battery system is the most important energy storage system with readily convertible chemical energy [2]. Over the past decade, many new technologies have made perceivable impacts on battery capacity and power density. However, further development is needed to incorporate excess storage capacity and significant balance of systems to meet functional requirements, and to reduce catastrophic failures [3,4]. In addition, advanced sensing and monitoring technologies are needed to predict and control battery functionality to identify, and further avoid, potential health issues.

Battery health issues can be categorized in two levels: system level, and cell level. System level issues are mainly affected by battery dynamic operation conditions as well as complicated electrochemical processes. Recently, battery prognostics addresses two critical issues:

- *Uncertainty* of battery behavior and internal characteristics. As a non-linear and time-variability system, the battery internal electrochemical process is nearly impossible to observe. Most battery state parameters, which control battery performance during design, manufacturing and usage, are usually subject to interference from dynamic ambient environment. Even basic charge and discharge processes are affected by the environmental conditions in terms of phase change reactions and

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chemical materials. The misunderstanding of battery characteristics and the performance state causes substantial issues for battery management and impacts the mobility of an EV or HEV.
- *Safety* assurance. Newer types of batteries, such as Li-ion batteries, have higher energy density, therefore they are more prone to safety issues if any faults take place. When high electricity flows, and the battery temperature increases to several hundred degrees within seconds, the increase in temperature will spread to neighboring cells, resulting in the battery catching on fire or explode [5].

One of the most critical steps for developing battery prognostics solutions is to establish a battery model which enables the automaker to simulate battery behavior and interpret battery issues in a form that can be understood by users and designers. For the last several decades, many different models have been developed [6–11] with limited accuracy. Some researchers have attempted to develop mathematical models to capture the features of battery chemical reactions at the cell level in order to explain battery side reactions, chemical degradation, loss of active materials, and thermal dynamics during rest and increases in internal resistance. Models are established based on battery dependent variables such as concentration, potential, reaction rate, and current density. For example, under the concentrated solution theory [12], John Newman used Stefan–Maxwell equations to explain the mass and energy transport of each species for each phase and component of the battery cell [12,13]. This model can explain the side effects and heat released during relaxation. It also helps to understand the shape of the discharge curve. These types of models are frequently called electrochemical models and are frequently used to clarify misinformation about the battery failure modes consequence of battery cells that consist of different chemistries and follow different paths of degradation. As for macroscopic information, some other well-known electrochemical models like Peukert's Law and Shepherd's model described battery electrochemical behavior in terms of voltage and current changes [14,15].

Electrochemical model development for battery systems has been making great progress by simulating system responses under nominal operating conditions. The required energy and power contents of the storage system, which determine the desired number and life span of the type of battery cell, can be derived. The models support the investigation of battery failure diagnosis and thermal effects specifically for cell assemblies and battery pack systems. However, this type of model does not directly lead to immediate understanding of system level battery behavior under dynamic discharge rates and inconsistent temperatures, or directly address state of charge (SoC) and state of health (SoH) estimation. Uncertainty of battery internal characteristics due to complex operating environments consequently make the performance observed at cell level hardly translated to that observed at the system level. Although these models attempt to build a good fundamental understanding of the electrochemical process, they are still far from being applied in practice [16–21]. Other researchers take advantage of theoretical explanations of battery behavior from the electrochemical models and integrate them with battery system issues of SoC and SoH modeling, which has been claimed to provide more accurate results than simple mathematical theories [22–24].

In contrast to the goal of achieving profound understanding through modeling of complicated electrochemical processes at the cell level, at system level, researchers are trying to simply model battery performance using electrical circuits [9]. Simplified electrical circuit models take direct usage of observable output of battery systems and are able to accurately estimate battery performance. They enable the ability to determine the response of a system as a whole. Over the last twenty years, researchers have created many equivalent circuit models for the battery. All of these models use an arrangement of voltage sources, resistors and capacitors to simulate battery performance [25,26]. The charge storing capacity of the battery is often represented by a capacitor. Other models employ a capacitor in parallel with a resistor (to show internal resistance) to model the transient response of battery voltage which a steady state model would not otherwise predict [10,15].

Most of these models are targeted toward achieving an accurate state of charge estimation. However, when encountering the issues of capacity fade, thermal influence, and energy density changing, most often these models neglect the impact of degradation and are not able to aid in understanding the interactions between components [11]. What is missing for most of these models is any consideration of the reliability of the electrochemical devices. Their life and the associated failure mechanisms are strongly dependent on their architecture, load profile, and control strategies [11]. Particularly, the influences of uncertainty in the load profile during dynamic battery operation are not considered in typical electrical circuit models. This limits their contributions in real EV applications, though they are widely employed during system design. Consideration of dynamic operation and the complexities of the circuit models are critical in EV applications. The other approach concentrates on taking full use of battery data during operation to estimate battery energy storage level based on a simplified electrical circuit model. The utilization of data-driven prognostic technology would compensate for the accuracy loss in utilizing a simple battery model. Many researchers have started to focus on combining the aforementioned circuit model with advanced data-driven prognostic techniques. Both historical data and online monitoring information of the system are used to train advanced machine learning tools for battery performance prediction, detection or estimation [27].

In summary, battery prognostic technology mainly includes advanced battery performance modeling methods and supplementary data-driven tools. Both techniques have been significantly

**Table 1**
List of all abbreviation.

| Abbreviations | |
|---|---|
| ADVISOR | Advanced vehicle simulator |
| ANFIS | Adaptive neuro-fuzzy inference system |
| AR | Auto regressive |
| ARMA | Auto regressive moving average |
| AUKF | Adaptive unscented Kalman filter |
| BMS | Battery management system |
| CDKF | Central difference Kalman filter |
| DoD | Depth of discharge |
| DST | Dempster–Shafer theory |
| EIS | Electrochemical impedance spectroscopy |
| EKF | Extended Kalman filter |
| EV | Electric vehicle |
| FEM | Finite element method |
| FVM | Finite volume method |
| HEV | Hybrid electric vehicle |
| KF | Kalman filter |
| NN | Neural network |
| NREL | National Renewable Energy Laboratory's |
| PHM | Prognostics and health management |
| RNN | Recurrent neural network |
| RUL | Remaining useful life |
| SoC | State of charge |
| SoF | State of function |
| SoH | State of health |
| SPKF | Sigma-point Kalman filter |
| SVM | Support vector machine |
| UKF | Unscented Kalman filter |

developed in recent decades for their capacity to enhance accurate energy storage estimation, facilitate entire battery management and reduce the uncertainty caused by dynamic operation conditions. This paper seeks to review battery prognostic technologies and elaborate on major unmet needs in the battery health monitoring for battery manufacturers, car designers, and electric vehicle drivers. Presented are a number of approaches that have been developed to monitor battery health status and performance as well as the evolution of prognostics modeling methods. It is a primary goal of this review of these methodologies to render such feasible and cost effective solutions for dealing with battery life issues under dynamic operational conditions.

In Section 2, challenges in developing and deploying prognostic technologies for batteries are introduced based on an overview of the battery aging process, measurable variables, and performance-affecting factors which influence battery degradation. A general perspective of battery prognostics issues, including battery state of charge (SoC) estimation, and battery state of health (SoH) prediction, are presented in Section 3. Section 4 reviews two main research thrust areas of battery prognostics, including data-driven, physical-model, and fusion approach. Furthermore, the characteristics, advantages and drawbacks of each approach are discussed. Section 5, from market level, reviews how battery prognostic technology contributes to widely concerning issues. For example, how the technology contributes to detect the onset of catastrophic failures, improve battery reliability, and safety. To facilitate better understanding of the abbreviations used throughout this paper, the list of all abbreviations is presented in Table 1.

## 2. Issues and challenges of battery health

Developing and deploying prognostics technologies for batteries is challenging and complicated due to the inherent complexity of the electric-chemical processes that occurs within batteries. In addition to difficulty in modeling at the cellular or system level to simulate battery behavior, limited information is available from real EV applications to establish or validate these models.

### 2.1. Issues of battery aging

Aging processes are irreversible changes in the characteristics of the electrolyte, anode and cathode and the structure of the components used in the battery. The battery aging process can be classified into two categories: aging processes that involve gradual degradation over time that is possible to be monitored, and those which do not have any specific mode or observable sign until a major problem or rapid changes in battery performance occur. An example of this is dendrite formation in lithium-ion batteries [28]. When a battery ages, tiny particles of lithium create a fiber structure—known as dendrite—on the battery's carbon anodes that can cause a battery fire. Once that happens, short circuits can take place and it causes a sudden rises in temperature and catastrophic failure of the battery. Such sudden changes can be considered as an important safety issue in batteries. However, this review will focus on gradual performance loss in batteries [29,30].

### 2.2. Degradation factors

How the battery is operated determines its performance and degradation mechanisms. Wenzl et al. [28,31] has published a detailed discussion and analysis concerning stress factors from the operating environment and how they can influence battery life and degradation. Stress factors are defined as statistical factors or adjusted scalar variables which are obtained from the time series of battery operating variables such as voltage, current, temperature, and SoC [28,32].

Several researchers have previously attempted to characterize battery degradation factors, and specifically to quantify the effect that these factors have on battery remaining useful life (RUL), as well as how they can contribute to battery modeling [28]. Considering literature in this area [28,30,33–39], the most significant degradation factors in automotive application can be identified as:

- Environment temperature
- Discharging current rate
- Charging rate (fast charging)
- Depth of Discharge (DoD)
- Time intervals between full charge cycles

Fig. 1 shows the most common current and voltage range at which the Li-ion battery operates. The *x* axis represents the current based on battery nominal capacity (C-rate) and the *y* axis shows the voltage ($v$). The discharge process is exhibited by positive current values, while negative current values can be equated to charging or regenerating processes. If the voltage of battery rises above the maximum defined charging voltage, overcharge will take place; if it goes lower than the defined cut-off discharge voltage, over discharge will occur. Therefore, there are two critical thresholds (gray zones), which are defined based on the type of Li-ion battery (for example, the maximum voltage for $LiCoO_2$ is 4.35v, and the maximum voltage for $LiFePO_4$ is 3.7v) [40]. Batteries have been designed to work in the acceptable range so any over charge/discharge can accelerate battery degradation and shorten life. However, the degradation rate of the battery in the acceptable range is not constant and depends on the rate of charge or discharge (stress factors). Typically, the discharge rate is very dynamic and directly depends on the operating condition. In fact, the discharge rate depends on the slope of the route, the weight of the car, and the speed and acceleration of the vehicle. In most cases, EV designers set a threshold to limit the maximum discharge current rate. During the charging process, the rate of charge remains fairly constant. A higher charging rate can charge the battery faster, on the other hand it can also reduce battery life [41]. Therefore, designers attempt to strike a balance between the charging rate and the impact that this rate can have on the life of the battery; this balancing process influences the rate of charge available in charging stations (like level 1 and level 2) [42]. The battery management system (BMS) limits this rate during charge process. Moreover, the battery charging process is very sensitive to the environmental temperature. Fig. 2 shows the best range of the temperature for charging Lithium based batteries. In Ref. [39] the authors show that the effect of ambient temperature on the battery cycle life can be reflected by film growth on the electrode. Low temperature reduces battery life due to a resulting increase in internal resistance, however, in higher temperatures, not only does the life of battery decrease, but also the risk of catastrophic failure is greater, which is a critical safety issue. For example, Dubarry et al. [43] did an experiment on two $LiFePO_4$ cells at 25 °C and 60 °C. The experiment shows that $LiFePO_4$ resistance for the battery at 60 °C is five times higher than a battery tested at 25 °C.

### 2.3. Challenges of monitoring battery health

Since the complicated electrochemical processes in batteries are physically hard observe by any direct measurement, most battery monitoring solutions are based on recognizing the critical variables which are observable during operation, and providing accurate and practical information about internal battery chemical reactions.

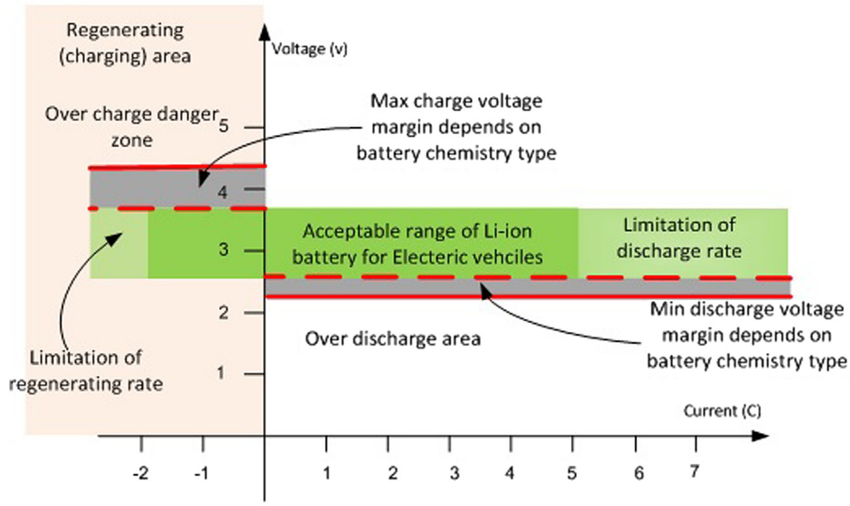


**Fig. 1.** Discharge and charge rate stress factors on Li-ion batteries [40].

These monitored variables can contain information that is potentially related to battery issues, either measured at cell or package level, on a continual basis [46].

Some researches establish prognostic modeling based on variables continuously collected or measured from a designated experiment cycle in which the battery is subjected to a defined testing procedures under stable conditions. These variables include voltage ($V$), current ($I$), internal battery resistance ($R$), battery temperature ($T_b$), ambient temperature ($T_a$), and operation time ($t$). This approach can help to avoid noise in the collected data, as well as uncertainty in the measurements from unexpected battery behavior which cannot be measured during full charge and discharge stages This approach can provide much more accurate and functional estimation of battery health status. The major drawback of this method is that it cannot be done online during normal battery operation.

In most real in-field applications, the most effective and simple method of monitoring battery behavior is based on observing battery voltage, current, temperature, and in some cases pressure. Some of these variables can be measured during battery operation without interruption of the main functionality of the device; this is referred to as online measurement [47–50].

These online measurements in reality suffer from signal noise, disturbances and poor quality, which can be a result of degraded sensors from harsh working environments. Therefore, the prognostic effort of estimating the battery health from online monitoring can lead to inaccurate results. Another issue with this approach is that these variables are dependent on the precision and accuracy of the sensors being used, which can have an impact on any monitoring or prediction results. For example, when a voltage sensor has a low accuracy such as $\pm 0.1$ V it cannot capture any changes within 0.01 V, which can affect the impedance calculation [51]. In addition, depending on the functionality of the battery, the battery pack might be required to respond to a power outage within milliseconds or seconds to evade loss of significant data. In these cases, data acquisition systems should be able to record raw data at a high frequency. Otherwise small errors will accumulate over time, negatively impacting the accuracy of results—particularly in determining the state of charge.

### 2.4. Consideration of features for monitoring battery health

The raw data available from a battery will usually contain specific behavioral patterns that can be seen in features. From the raw data, many features can be extracted. Not all features will be degradation-related features, which are specific features in the raw data that will change with battery internal chemical element density variation. The most useful features should represent noticeable trends during battery performance, and can be linked

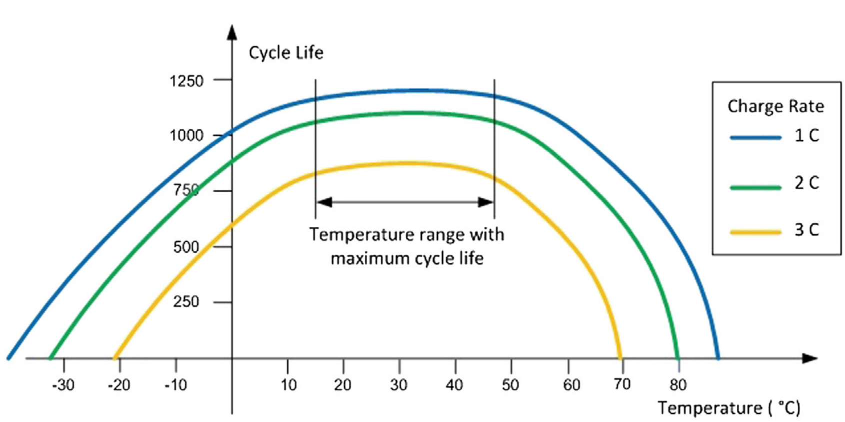


**Fig. 2.** Lithium ion battery life vs. temperature and charging rate [36,39,44,45].

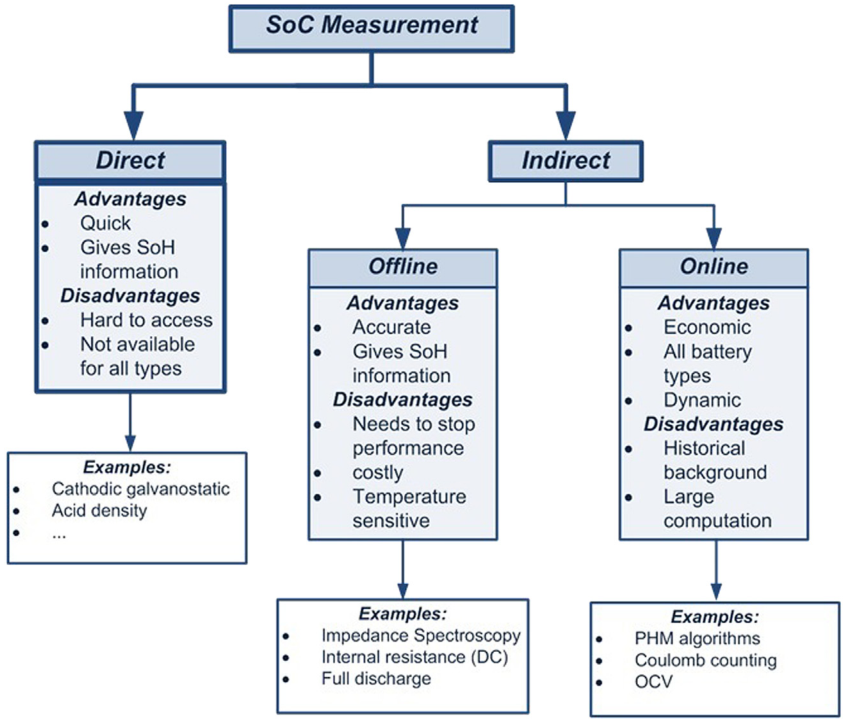


**Fig. 3.** The most important SoC estimation methods [60,61].

with the physical causes of degradation based on electrochemical reactions inside the battery. Their life and the associated failure mechanisms are strongly dependent on the architecture, load profile, and control.

## 3. Prognostics of battery health

### 3.1. Overview of battery PHM technologies

Prognostics and health management (PHM) is an emerging science consisting of tools and techniques to evaluate the reliability of a component or system in its real life cycle conditions so as to determine the initiation of failure and mitigate system risk. It gives attention to predicting the future condition of a product or a system [52].

The phrase "battery PHM" has a wide variety of meaning, ranging from irregular manual measurements of voltage and electrolyte specific characteristics to fully automated online observation of various measured and estimated battery parameters. In the electric vehicle application domain, researchers have looked at the various failure modes of the battery subsystems. Different diagnostic methods have been evaluated, like discharge to a fixed cut-off voltage, open circuit voltage and electrochemical impedance spectrometry (EIS) [53]. Therefore in this case, the crucial questions reduce to whether the battery will provide the required power during the driving operation, what kind of degradation processes are at operation, and how many more years this battery can support. These concepts are summarized in the terms state of charge (SoC) and state of health (SoH) [54]. This section elaborates these concepts and similar phrases for electric vehicle batteries. There are different methods and techniques to estimate battery SoC and SoH [55,56]. In this paper, these methods have been classified into three main groups: data-driven, physical-model based, and fusion model approaches [57]. All of these approaches will be explained in detail in Section 4.

### 3.2. State of charge estimation

Battery state of charge (SoC) estimates the amount of energy remaining in a cell compared with the energy it had when it was fully charged, and gives the user an indication of how much longer a battery will last before it needs recharging. In electric vehicle applications, SoC works like a fuel gauge in a car. Therefore, the accurate estimate of SoC is the significant factor and it can have an influence on battery health and safety over time. However, the SoC estimation is not an easy task and it depends on the battery's chemistry and condition. Typically, SoC estimation is classified into two main categories: direct measurement and indirect estimation [58]. In fact, there are few methods to measure SoC directly from the chemical and physical properties of the battery, such as electrolyte PH, density measurements and cathodic galvanostatic pulses [22,59]. However, measuring these variables requires accurate measurement devices, which can be expensive, and have limited applicability in practice because it is difficult, and sometimes impossible, to have access to materials inside the battery. To avoid these difficulties, indirect SoC estimation has been developed. In this category the variables which can be measured directly from the battery such as current, voltage, and temperature are going to be used to provide an accurate estimation of SoC. Fig. 3 shows the summery of SoC techniques classification with some preliminary examples [60,61]. However, SoC has a non-linear relationship with these parameters.

Generally, SoC can be estimated from direct measurement variables in two ways: offline and online. In offline techniques, the battery needs to be charged and discharged in a specific way to be able to extract features from the acquired data. Most often, offline methods give accurate estimation of battery SoC, however they are time consuming, expensive, and interrupt main battery performance. These are the main reasons that researchers are conducting research on methods and techniques for online estimation of SoC [62–66]. The most common method of SoC calculation is Coulomb-

counting. Equations (1) and (2) show this relation in charge and discharge processes:

$$\mathrm{SoC} = \mathrm{SoC}_0 + \frac{1}{C_n} \cdot \int_{t_0}^{t} |I| \cdot \mathrm{d}t \quad \text{Charge} \tag{1}$$

$$\mathrm{SoC} = \mathrm{SoC}_0 - \frac{1}{C_n} \cdot \int_{t_0}^{t} |I| \cdot \mathrm{d}t \quad \text{Discharge} \tag{2}$$

where $C_n$ is the nominal capacity of the EV battery pack, $I$ is the battery current, $\mathrm{SoC}_0$ is initial SoC and, $dt$ is the time interval. However, this method needs an accurate measurement of current ($I$) and historic knowledge of initial $\mathrm{SoC}_0$. Thus researchers have used a variety of prognostics techniques to provide accurate estimation of battery SoC in practice [60,61].

### 3.3. State of health assessment

It is important to distinguish between remaining useful life prediction and battery health condition. Battery cycle life is defined based on battery type, material and standard usage by battery manufacturer in the term of how many cycles it can support. The concept to represent the specified performance and health condition of a used battery compared with a brand new battery of the same type is called state of health (SoH) [67]. Gradual deterioration of battery performance is caused by irreversible chemical reactions and leads to capacity fading and reduction in the remaining useful life. Although it is possible to determine SoC by measuring current and time, there is no fixed definition for SoH and each manufacturer has established their own. Different features from the battery can be utilized to identify SoH such as capacity and internal resistance, but it is an assessment and judgment rather than accurate measurement [68–70].

Establishing the SoH makes sense for batteries that are in use and have started their degradation process, however, manufacturers cannot currently determine the SoH before a battery enters service. In this case, prognostics and health management can play an important role to define SoH of battery based on different aging processes [71]. Any parameter that changes considerably with usage, such as internal resistance and capacity, can be used as a basis for providing an indication of the SoH of the battery. Changes to these parameters normally indicates that another alteration has occurred which may be more significant to the consumer. These could lead to deviation in the battery performance, such as a rapid loss of power; or a sudden rise in temperature throughout the operation; or internal degradations such as passivation of the electrodes, gassing, and corrosion [69,72].

Prognostics and health management systems need to maintain a record of features from the health condition. In lithium-ion cells, the number of charging/discharging cycles, capacity, and internal resistance are used as a measure of battery usage. If any of these measurements provide marginal readings, the end result will be affected. A cell may have ample capacity during operation while the internal resistance is high. In this case, the SoH estimation is not accurate enough, because it will depend on which feature has been used. To deal with this problem, state of function (SoF) is used to define the performance of a battery during operation based on each application.

SoF takes into consideration the weight of range of SoC, the charging/discharging rate, the environmental temperature and other degradation influencing factors [73]. In fact, how the battery performance meets the real power demands during battery operation is expressed by state of function (SoF) [70,74,75]. One of the methods to determine SoF is to calculate the ratio of the remaining accessible power in the battery module and the maximum possible power which could be stored in the pack [73]. The main issue is that once the battery is in the system, which needs particular amount of power supplied, not all stored energy in a battery is usable. Even if a given set of SoC and SoH is known and close to 100%, there are some barriers that do not let the user to utilize the entirety of the energy that has been stored in a battery. Fig. 4 shows a relation between SoF, environmental temperature, and charge/discharge rate for a lithium-ion battery employed in EV and PHEV. If the battery discharges with low current, even if the internal resistance is high, the voltage drop is negligible, therefore the SoF is near 100%. However, by raising the discharge rate, the amount of energy that can be used from the battery will increase proportionally to the value of internal resistance and voltage drop. Since the internal resistance of battery is higher in low temperature, by reducing environment temperature the functionality of battery will decrease quickly (Fig. 4). The gray rectangle shows the most usable range of discharge rate in EVs. Demanding a very high level of power from a battery pack will reduce SoF, quickly reaching the SoF threshold. This is the reason that in most EVs, the battery management systems (BMS) have been configured with a specific threshold that will not let the user demand more power from the battery.

Battery functionality during the charge process is more sensitive. Standard charging processes (level 1 and level 2) use currents in the range of 16 A–80 A (SAE J1772) [77]. According to different EV's battery nominal capacity, this range is between 0.5 C to less than 2 C [77]. The main reason to keep batteries at a low charge rate is to have good control on battery balancing between cells. A high charge rate will increase the gap of voltage between a cell with low internal resistance and a cell with high internal resistance. Thus by increasing charge rate, the battery's SoF reduces faster than its discharge rate when there is a constant environmental temperature [19,78,79].

## 4. Techniques for battery prognostics

### 4.1. Physical-models approach

The simple internal resistance battery model ($R_{int}$ model) was implemented and tested in the National Renewable Energy Laboratory's (NREL) advanced vehicle simulator (ADVISOR) in 1994. It consists of an ideal battery with open-circuit voltage ($E_O$) and a constant internal resistance ($R_{int}$) [80]. The measurable terminal voltage ($V_o$) can be acquired from the open circuit voltage and ($R$) can be attained from both the open circuit measurement and one extra measurement with load associated at the terminal when the battery is fully charged [81–84]. Although this model has been extensively used due to its simplicity, it does not take into account the varying characteristics of the internal impedance of the battery with the varying state of charge, electrolyte concentration and sulfate formation. Such a model is only valid under steady state load conditions since its voltage response to load changes is too responsive [80].

#### 4.1.1. Thevenin model

As batteries are being applied to various electrical systems where the load is more dynamic, the $R_{int}$ model is not sufficient to make accurate predictions of the behavior of batteries. In order to simulate the dynamic behavior of batteries, Thevenin model was developed based on Thevenin theory. Fig. 5 shows the Thevenin model in a basic form. It includes resistors and a RC network in series to forecast battery response at a particular state of charge and

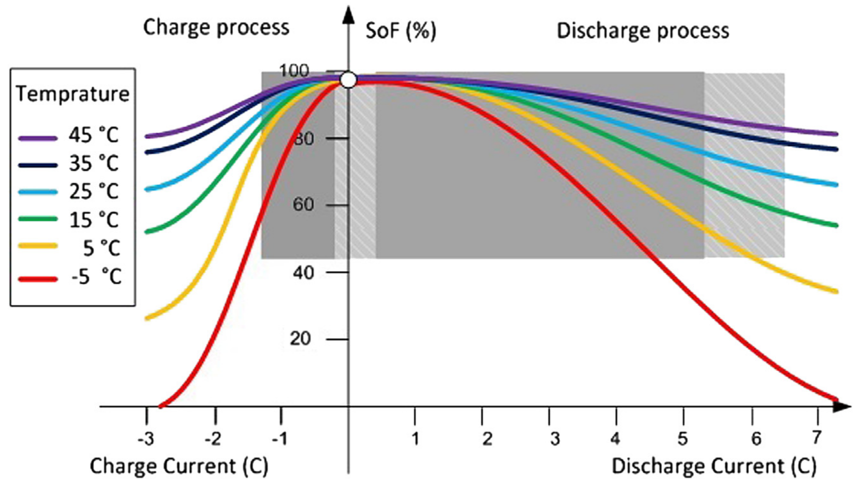


**Fig. 4.** SoF changes vs. charge/discharge rates and environment temperature [34,39,73,76].

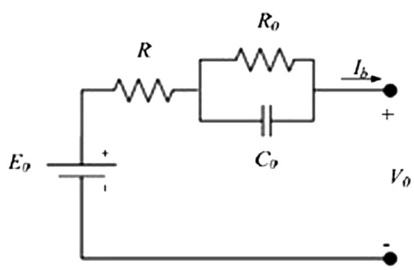


**Fig. 5.** Thevenin circuit model [85].

assuming that the open circuit voltage is constant [10]. As compared to the $R_{int}$ model, Thevenin model is capable of predicting the battery's voltage transient response due to a change of current load, and thus can be applied in more dynamic conditions. The accuracy of Thevenin to predict the dynamic behavior can be improved by adding more RC networks. Thevenin model with three pairs of RC circuits can simulate the short-term transient response (in seconds), mediate term transient response (in minutes), and long term transient response (in hours) [50,66].

As the study on batteries goes deeper, it was found that the basic Thevenin model was not capable of explaining all batteries' behavior. For instance, the resistors in basic Thevenin model are assumed to be constant for both charge and discharge process, which may not be correct in the real world. In 1992, Salameh improved the basic Thevenin model by adding ideal diodes in series with the resistors to differentiate their values in the charge and discharge process [85]. The zener-diode model is also developed based on the Thevenin model by adding a zener-diode in parallel with the long-term response RC network. Abu-Sharkh and Doerffel [86] proposed this model in 2006. In their studies, they proposed a rapid test method to measure the open circuit voltage and internal resistance of a battery. During their experiment, they observed a constant voltage change during a long-term transient response between a 10% and 90% SoC level in both charging and discharging processes. This phenomenon is very similar to a zener-diode and the constant voltage drop can be modeled as zener knee voltage (shown Fig. 6) [86].

The main drawback of the Thevenin-based battery model is that all the units are assumed to be constant, but in real applications, all parameters may vary as functions of working conditions and battery usage history [11]. Moreover, the Thevenin model is not capable of simulating the runtime of the battery or the capacity fading due to thermal and degradation impacts [10].

#### 4.1.2. Runtime-based electrical model

As batteries are being applied to more energy intensive systems such as Electrical Vehicles, the information about batteries' capabilities and duration becomes very important. In 1993, Hageman

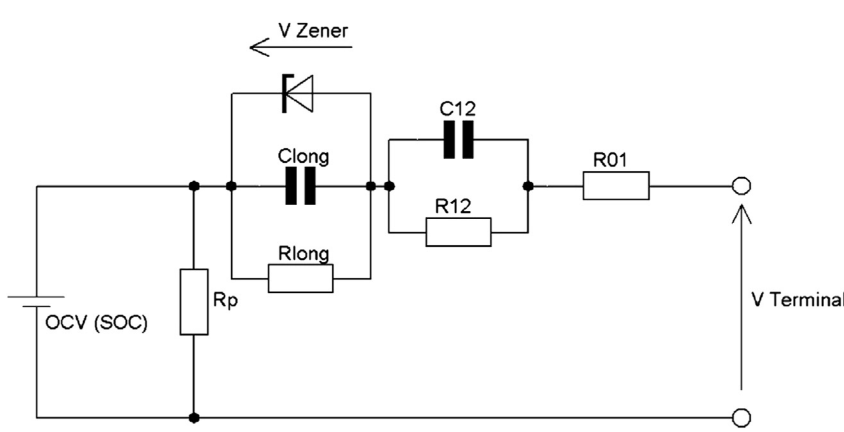


**Fig. 6.** Improved Thevenin model [86].

proposed the runtime based model as shown in Fig. 7, and performed simulation on PSPICE [87]. The runtime base model uses a complicated circuit networks to create battery runtime and DC voltage response for a constant discharge current. An advantage of this model is the ability to simulate the capacity fading due to factors such as thermal effect and aging. In Hageman's study, he considered the effect of varying temperature on battery capacity. In his simulation, he set the capacity at 25 °C as the initial capacity to calculate the capacities under different temperatures for different battery types [88]. However, this model can predict neither runtime nor voltage response accurately under dynamic load conditions [10].

#### 4.1.3. Combined electric model

In order to simulate the voltage response and battery runtime, while taking the impact of battery degradation and thermal effect into consideration, Chen and Rincon–Mora proposed the combined electrical model in 2006. As shown in Fig. 8 [10], this model is a combination of a runtime model (left part) and RC networks similar to Thevenin-based models (right part). The capacitor and the current-controlled current source are used to model the capacity, SoC and runtime of the battery. The RC networks are capable of simulating the transient response of the battery's terminal voltage under dynamic load conditions. In this model, the battery's usable capacity is no longer considered infinite or constant, but as a function of cycle numbers, battery temperature and storage time (self-discharge) [10,50,89,90]. Since the open-circuit voltage is a function of SoC, the voltage-controlled voltage source is used to modify its value according to varying SoC values. This model considered two RC networks to represent the voltage transient response of two different time constants to balance the complicity and accuracy. In spite of its ability to predict runtime and dynamic behavior of the battery with relatively high accuracy, this model is still not able to predict the batteries' state of health (SoH) and self-update the parameters. Hence, the prediction results will be less and less accurate as the battery degrades.

While some information of a battery can be obtained from direct measurements, the hidden information such as SoC and SoH are buried in a massive amount of signals and need to be estimated. Before intelligent algorithms can be applied to estimate the invisible information, a good understanding of battery behavior should be established. The process to develop an equivalent circuit model is one of the paths to understanding battery behavior. The different battery models as described here have built up the foundation to develop linear space equations in battery prognostics. To make decisions on which model to use in practical analysis, one should consider on which specific battery types a model can be applied, and the desired balance between accuracy and simplicity.

### 4.2. Data-driven approach

Data-driven techniques generally learn from historical data of the system and then wisely suggest a decision through results. In this method, there is an important assumption that the data condition and regime remains constant until a system (e.g. a battery) fails [57]. Pecht & Jaai classified this technique into three categories based on what type of labeled data is available: supervised learning when both healthy and faulty data is accessible; semi-supervised when just one of the classes is known; and unsupervised when no labeled data is available. The techniques and algorithms should be flexible to provide suitable results for each of these three categories [91]. One of the benefits of data-driven approaches for electric vehicle batteries is that they can be applied as black-box models, as they are capable of learning the behavior of the battery based on monitored vehicle data and thus do not demand battery chemical modeling and knowledge. This is because data-driven approaches can be used to model the relationship between battery performance and environmental parameters during operation. Prediction of SoC and SoH can be accomplished using a variety of data-driven techniques. Several of the most practical techniques are reviewed in detail below.

#### 4.2.1. Neural network

Current studies in time-series forecasting have focused more attention on the use of flexible techniques such as neural networks (NN). The main advantage of NN methods is that they are established automatically by training, without the need for the detection of model parameters and coefficients. Feedforward and recurrent are the two types of NN architecture design, both of which have been utilized in time-series prediction systems. The feedforward network has been categorized as a type of non-linear auto regressive (AR) model, and recurrent network as a non-linear ARMA (Auto Regressive Moving Average) model. This comparison suggest that recurrent has more advantages over feedforward just as ARMA has advantage over AR models [92].

In neural network applications, it is important to design the number of neurons in each hidden layer and define what they represent. Researchers have utilized this method for both SoC estimation and predicting the available capacity. For example, Yamazaki has used four neurons as an input which they indicate terminal voltage, battery temperature, internal resistance, and discharge current [79]. In the output, SoC with 10% step has been

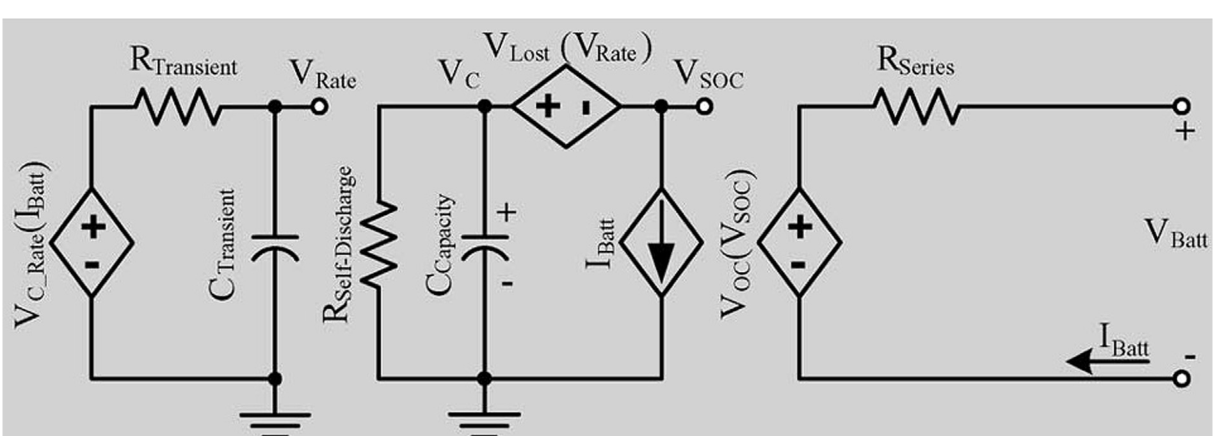


**Fig. 7.** Runtime-based electrical base model [10].

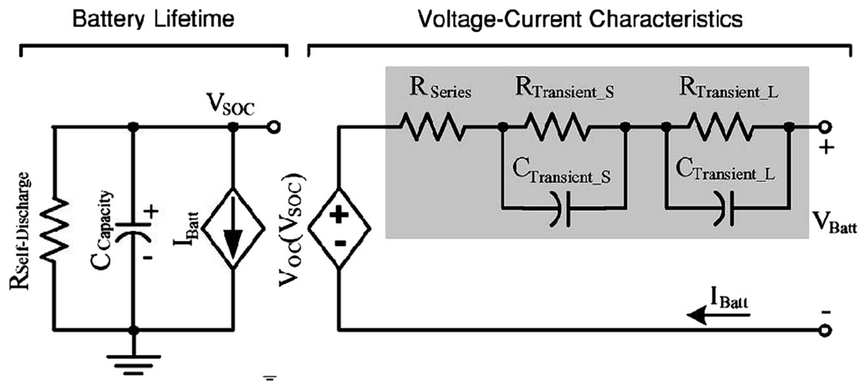


**Fig. 8.** Combined electrical model [10].

represented by 10 neurons. Shen has used 7 neurons as an input layer, the first five of which are discharge capacity for five current ranges; the sixth neuron represents regenerative capacity for regenerative current and the seventh one represents temperature. Back propagation algorithm was used and the state of available capacity was calculated as an output, which shows a 2% error regarding the experimental data obtained from such a complex condition [93].

Since battery performance degrades over time, there is a relation between existing $SoC_t$ and the previous $SoC_{t-1}$. Therefore, the previous $SoC_{t-1}$ can be interpolated as an input variable [94]. The same logic has been used to estimate remaining useful life of a battery by inputting the capacity of the previous cycle to predict the capacity for the next cycle, according to the lab experiment data set [95]. Linda et al. [96] followed the same logic, using voltage and current. Three steps of voltage and current (including existing step and steps $(t-1)$ and $(t-2)$), plus the current ambient temperature, are considered as input to train the model, the output of which is the SoC. Charkhgard et al. [97] has introduced radial basis function (RBF) for neural network. In this case voltage was used at the sampling time $(t-1)$, SoC and current at sampling time $(t)$ as three inputs, and voltage at the sampling time $(t)$ as output to train the model. The NN was then used as a model in extended Kalman filter (EKF) to estimate SoC (Kalman filter is explained in details in Section 4.3). However, Chen et al. [82] combined EKF and NN differently and used SoC at sampling time $(t-1)$ as an input for the neural network model, after it has been estimated from EKF. Andre et al. [98] has compared both EKF and NN to estimate SoH of battery. This comparison confirms that EKF was simpler to apply, needs less input values and requires no functions of the dependencies to the working environment. In fact, the NN needs recognized correlations among the input variables and internal states. Specifically, if a large number of vehicle data is available and can be utilized for offline training, the NN points out its advantages compared to an EKF in terms of memory usage and calculation speed, and should be favored. Quite the opposite, due to high computational needs, EKF is not a good choice for an online estimation, however, because of fast adoption of filter it can be used in the cases with low number of training data sets.

When the mathematical link among variables is unidentified, or when there are few input data for interpolation, it is proper to use a recurrent neural network (RNN) [99]. In other words, the main advantage of RNN is that it is able to present dynamic modeling of the voltage and SoC at the same time. Capizzi et al. [99] used RNN to predict state of charge and battery terminal voltage and then to estimate mathematical battery model parameters. Another application of RNN is using that one to reach accurate results and to develop a better battery model. Monfared et al. [100] implemented RNN to estimate the parameters of the equivalent battery model for a lead acid battery. The model has six parameters including three resistance, one inductor and two capacitors. The comparison results shows less than a 1.7% error of estimating three resistances by RNN comparing with experimental data and a 0.45% error for the inductor and a 6.7% and 9.5% error for the two capacitors, respectively, which is acceptable.

*4.2.2. Support vector machine*

In different domains of pattern recognition SVM has been used for classification and regression. According to [101] prediction analysis based on regression, it is more complicated than classification by using SVM. In a neural network, the experimental training error is minimized, however it still includes several disadvantages, like how to select the number of hidden layers and some local minima solutions, but SVM is able to diminish the upper bound of the generalization error by optimizing the margin between the separating hyper plane and the data. The basic idea to use SVM to determine the regression model for state prediction is mapping the data in input space, and transforming them into a higher dimensional feature space using the non-linear transfer function. And fit the sample data in the feature space using a linear function [102]. In the SVM technique implementation, the problem can be described as an optimization problem of linearly constrained quadratic programming. Typically, the core idea of SVM is to map the input data $x$ into a countless or high feature space using a non-linear mapping $\beta$ and to do linear regression in this space. As an example, a sample of N point $\{x_k, y_k\}$ with input vectors $x_k \in R^n$ and output values $y_k \in R^n$ is given [103]. The main objective is to estimate the model of the form:

$$y = \alpha^T \cdot \beta(x) + s \tag{3}$$

where $\beta(x)$ is the mapping to a countless dimensional feature space; $\alpha$ is the weight vector which has the equal dimension with kernel space and $s$ is the bias expression. In the case of battery it is very significant how to formulate these terms with battery variables and outputs [104]. The principle to use SVM for SoC prediction is to model the battery's non-linear dynamic for both charge and discharge processes. The advantages of using SVM include its high generalization ability, non-demanding requirement for sample size, and good performance in dealing with high dimensions and non-linear models. If the SVM parameters are determined properly, the results can be relatively accurate. The SVM developed to use current, temperature, and SoC as input to predict output of load voltage yield a maximum relative error of 3.61% [102]. Nuhic et al. [105] has developed SVM model to identify battery SoH for electric cars. Nuhic has divided the available data into 2/3 of the data being

for training and 1/3 of the data being for testing and predicted SoH with less than 0.0007 mean square error in real driving conditions considering temperature change, SoC and C-rate.

#### 4.2.3. Fuzzy logic

One of the suitable ways to describe a definite conclusion from complex or unclear data is fuzzy logic. It looks like a decision making system to discover an accurate solution with its capability to work from imprecise data. By applying fuzzy logic it is not necessary to understand the whole system process and equations; however, it allows expressing a complex system using a superior level of abstraction which originates from experimental tests and real applications. A simple fuzzy logic learning system has been developed and implemented for state of charge estimation for rechargeable batteries [106–109]. For example, if a battery has 30% SoC, then people may be concerned with two concepts: full or empty. The notion of each of them can be corresponded to a certain fuzzy set, one might describe the battery as being 30% full and 70% empty. It is very important that the concept of emptiness would be subjective. Therefore another person might set a membership function where the battery would be considered full for all values down to 50%. It is important to understand that fuzzy logic uses truth degrees as a mathematical model of ambiguity while probability is a mathematical model of unawareness.

To provide appropriate data for the fuzzy logic model, various methods have been employed. Singh et al. [110] acquired electrochemical impedance spectroscopy (EIS) data for Ni–MH batteries over 28 cycles, which consists of real and imaginary values. For estimating SoC, real values at three different frequencies (10, 251.1 and 3981.1 Hz) plus imaginary values at just two frequencies (10 and 251.1 Hz) have been inserted as inputs and SoC has been considered as the output to train the fuzzy model. This model is able to forecast the SoC within ±5%.

Adaptive neuro-fuzzy inference system (ANFIS) is one of the methods that can be applied to any type of battery with different operating conditions, such as constant discharging and partial discharging, if trained before use [111]. The main advantage of the combined method ANFIS is that it can use the exact solution of the neural network, as well as heuristic knowledge of fuzzy logic; however, each of these methods are unable to provide individually [112].

### 4.3. Fusion approach

A critical issue with data-driven techniques is that when the data availability is not satisfied, or the data is biased, the results can be imprecise or even incorrect entirely. Furthermore, data-driven approaches usually require a well-implemented monitoring system to function which sometimes cannot be provided. Physical-model methods on the other hand are not as flexible as data-driven methods due to their reliance on the establishment of a physical-model, which usually requires a large amount of expert knowledge and system testing. However, when such physical-models are successfully implemented, they require much less data to perform accurate battery PHM. The results from physical-model methods are usually much more stable compared to those from data-driven methods because they are less sensitive to unexpected conditions and outliers.

In conclusion, data-driven and physical-model methods are potentially complementary to each other; therefore, it is desired to develop a fusion model combining the two approaches to achieve an optimal battery PHM solution [57]. With such combined model, the battery working in field can be better described and simulated, which will eventually provide a solid foundation for the fusion model approach. Several stochastic filtering techniques, which can be classified in fusion approach, has been applied on battery SoC and SoH estimation.

#### 4.3.1. Kalman filter

Kalman filtering (KF) is an accepted tool, which provides a theoretically well-designed and time-proven method to filter measurements of system input and output to produce an intelligent estimation of a dynamic system's state. It is in common use in many fields, including radar tracking, map-reading, and communication. The Kalman filter method uses the experiential input data and output data to find the minimum mean squared error assessment of the true state. The main assumption in Kalman filtering is that the measuring noise and process noise are Gaussian, independent of each other, and have a mean of zero. If the system is non-linear, a linearization process at every time step is employed to estimate the non-linear system with a linear time varying system. In these cases, the linear time series structure is used in the KF, leading to an extended Kalman filter (EKF) on the true non-linear system. The KF linear model is given by a process Equation (4) which is a linear function that uses the previous value of $x_{k-1}$ to estimate the current value $x_k$ and measurement Equation (5) which corrects the estimated value from process equation to converge it to the real value [113–116].

$$x_k = Ax_{k-1} + Bu_{k-1} + a_{k-1} \quad \text{process} \tag{4}$$

$$z_k = Cx_k + b_k \quad \text{measurement} \tag{5}$$

where $x$ is the system's state variable, $u$ is control input, $z$ is a vector used for comparison, $A$ is a covariance matrix that links $x_{k-1}$ to $x_k$, $B$ is a covariance matrix that links $u_{k-1}$ to $x_k$, $C$ is a covariance matrix that links $x_k$ to $z_k$, $a$ is process noise and $b$ is measurement noise. In battery PHM it is very important how to formulate battery variables with these basic equations. Di Domenico et al. [117] used this method to estimate battery SoC (instead of $x$ in Eq (3)) by measuring battery voltage (instead of $z$ in Eq (4)) and electrochemical models. Plett did extensive work to apply an extended Kalman filter (EKF) and apply it in BMS in his series of papers [118]. To apply EKF, he developed numerous models from preliminary to more advanced ones. In the advanced format, the model involves parameters for open circuit voltage, internal resistance, polarization time, electrochemical hysteresis, and the effect of temperature [119,120]. EKF also has been used to estimate the variation of capacity, which identifies the ability of the battery to accumulate charge over time, indicating capacity fading and eventually determining SoH [121].

In Ref. [122] current and terminal voltage has been used as input for the Kalman filter model. Barbarisi et al. [122] applied this technique on a 6.5 Ah Ni–MH battery to estimate SoC. Moreover, diffusion phenomena in an active material have been modeled so it is possible to get a good estimation of SoC during overcharge and over discharge phases. A combination of the RC model and the hysteresis model have been used by Vasebi et al. in Ref. [123] to compensate for the drawbacks of each model. The Kalman filter is then used to estimate SoC. The results show error is 2% less than coulomb counting methods.

As a substitute approach to state assessment for non-linear systems, Plett has applied a sigma-point Kalman filter (SPKF) for battery SoC estimation [124]. SPKF has a higher order of precision in estimating the mean and the error covariance of the battery state vector than EKF. Moreover, SPKF does not need the computation of the Jacobian matrices, and the computational complexity is similar to EKF [125]. The SPKF can be classified as two main methods: unscented Kalman filter (UKF) and central difference Kalman filter (CDKF). In Ref. [126] an equivalent electric circuit model has been

**Table 2**
Comparing advantage and disadvantage of data-driven, model based and fusion approaches.

| Technique | Advantage | Drawbacks |
|---|---|---|
| Thevenin model | Simple and easy to implement, | Resistance and capacitor assumed to be constant, cannot predict capacity fading |
| Runtime-based electrical model | simulate the capacity fading due to factors such as thermal effect and aging | Not good in dynamic load condition |
| Combined electrical model | Accurate in dynamic load condition | Weak in self-updating model parameters |
| Neural Network | Match with other techniques, Suitable for different battery applications | Needs lots of training data, depends on historic data set |
| Support vector machine | Suitable for different battery applications, good for diagnostic | Needs lots of training data, |
| Fuzzy logic | Formulating in human thinking way, Easily combine with Neural Network | Not enough accurate |
| Kalman filter | Accurate estimation of SoC, no initial SoC needed, Easily filter noise on data | Large amount of calculation needed, Complicated |
| Sliding mode observer | Simple control structure and robust tracking performance under uncertain environments, Fast SoC estimation, High accuracy | Slow time-varying observer for SoH |

used to develop UKF for estimating SoC. The UKF not only has been used to estimate SOC, but also it has been applied to evaluate SoH and SoF online. A CDKF for SoC estimation shows better accuracy than EKF based on the non-linear enhanced self-correcting battery model in Ref. [127].

Sun et al. [128] has developed an adaptive unscented Kalman filter (AUKF) to estimate electric vehicle battery SoC while it is on operation. This method can adaptively adjust the values of process and measurement noise covariances in the SoC estimation process. The AUKF is based on the zero-state hysteresis battery model, which causes the battery model to have a simple formation and the filter to have a low computational load as an advantage of SoC estimation [128].

*4.3.2. Other techniques*

Sliding mode observer is a new SoC indicator technique that has been introduced by Kim [129]. This method has been applied for accurate tracking under the non-linearity of the simple Thevenin model. Result validation in the urban dynamometer driving schedule test shows less than 3% error in SoC for most cases [89]. In the most advanced cases, the dual sliding-mode observer has been developed, which is able to estimate SoC and terminal voltage as a fast time-varying observer and estimate SoH as a slow time-varying observer [130,131]. He et al. [132] has proposed novel method by applying Dempster–Shafer theory (DST) to predict battery RUL based on capacity fading. In his method, the Bayesian Monte Carlo approach was adopted to approximate the model parameters and provide cell capacity prediction. This method can consider the measurement noise and dynamically renew the model parameters derived from new measurements so as to provide accurate estimations.

A summary of physical-models, data-driven models and fusion model used for battery SoC and SoH estimation is presented in Table 2. For each method, general advantages and drawbacks are explained; however, these methods can be combined with some other techniques for specific applications and therefore may exhibit particular characteristics not accounted for here.

## 5. Battery safety and reliability

Battery safety has significant consequences on systems' functionality and market acceptance. Customers would like to have worry-free devices or electric vehicles to run [133]. However, any news about battery fire or explosion can disturb this flourishing market [134,135]. The major problem with the Li-ion battery is the simplicity with which it can be broken during use: The Li-ion battery packs that are employed in EVs holds a massive amount of energy in a small package. Considerable high internal resistance increases the probability of the battery getting hot enough to burn or explode if the cell unexpectedly shorted.

Discharging a battery too far is another mistreatment of Li-ion batteries. The Li-ion cell should never be able to drop less than 2.40 V, or an internal electrochemical reaction will take place where one of the battery electrodes can corrode through a process which cannot be reversed by recharging. If this happens, battery capacity will be faded (and the cell may be completely destroyed). A similar process can happen if a Li-ion cell is charged to higher than 4.15 V. Therefore internal corrosion can occur if current is persistently forced into a fully charged cell, which will diminish cell capacity significantly. For this cause, Li-ion cells cannot be trickle charged for long time periods without cutting off the current when full charge is reached.

Accordingly, many approaches are being considered with the aim of dropping safety hazards. Most of the methods are supposed to depress energy release. Hence, the practical value of these approaches depends on whether an adequate compromise between demanded power and safety requirements can be achieved. At present, the safer lithium ion batteries are mainly used in electric and hybrid vehicles, where safety issues are significant. In this paper we are looking to see how PHM can help battery users and designers to extract useful features from key variables of the battery, like current, voltage and temperature, and interpret the level of safety based on battery operation condition. To reach this objective, first we look at battery safety mechanisms and then review how current PHM techniques can prevent EVs from catastrophic failures.

Lisbona & Snee [136] did extensive review on battery safety mechanisms and malfunction. According to their work, safety in EV battery pack is provided at three separate stages, as shown in Fig. 9.

1. At the *cell hardware* stage, safety mechanisms involve cell design features such as safety vents, shutdown electrolyte additives, current disconnect device and separator materials [137]. As explained by Takami et al. [138], these are necessary to avoid the occurrence or in some cases limit the extent of consequences of internal malfunction at individual cell and battery pack level. At this stage there are not that many applications for PHM techniques since mechanical devices perform on battery safety.
2. At the *system hardware* stage, a combination of some electromechanical devices and PHM techniques is employed to prevent

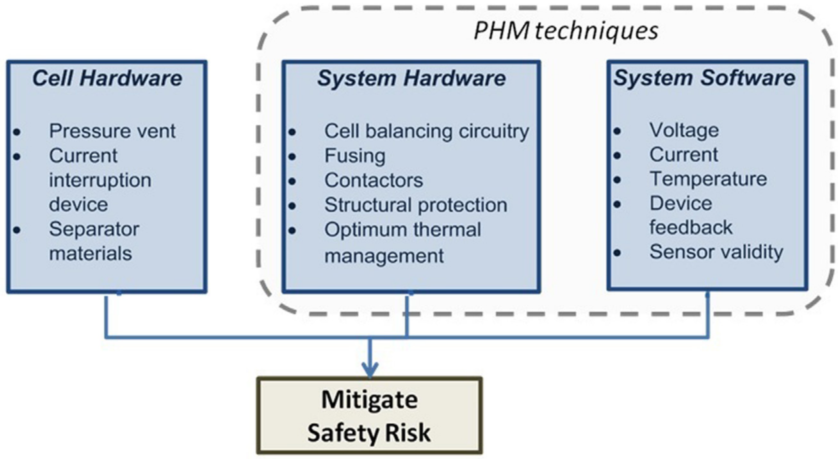


**Fig. 9.** Integration framework of safety factor from a battery pack [136].

batteries from catastrophic failures. A battery management system (BMS) is necessary to avoid overcharge and over discharge, as well as to monitor battery temperatures to detect overheating. Some PHM techniques can be applied on BMS to prevent these issues and mitigate safety risks. For example, accurate estimation of battery pack SoC by EKF is one application [139]. BMS also plays an important role to keep all cells balanced and detect abnormal cells among the pack. Zheng et al. [140] has applied Shannon entropy to diagnose low capacity and high resistance cells among the pack.

Fuses are essential hardware devices to protect against high current excursion in battery performance, and appropriate contactors reduce the risk of external short-circuit. Moreover, batteries have to be provided with a thermal management system (e.g. suitable ventilation) to prevent overheating during operation. Large capacity battery modules are created by tightly packing small commercial cells. Because of the high energy density of Li-ion batteries and self-heat generation during discharge, heat dissipation needs to be considered in module design.

Fig. 10 shows an experiment applied on a fully charged Li-ion battery and heated with the rate of 5 °C min$^{-1}$ from room temperature to 200 °C [141]. According to the graph, the self-heat generation can be classified into three stages: onset, acceleration and thermal runaway. In this example, an external source heated the battery to reach the 150 °C called onset temperature. During this time, the self-heat generated with the low rate of 0.2 °C min$^{-1}$, which can be dissipated in the battery pack. The region above onset is identified as acceleration heat because the heat is not dissipated and the temperature continues to rise because of exothermic reactions. The acceleration of self-heating in stage 2 is the main feature in PHM to detect the early stage of the catastrophic failure. Additional heating leads the cell to enter the third stage, called thermal runaway. Thermal runaway occurs approximately when the self-heating rate is 10 °C min$^{-1}$ or greater [141].

Thermal management of the batteries forming the pack and module is required to avoid spread of these self-heating thermal effects [142]. Battery packs and modules are normally managed using ventilation systems. Novel thermal management systems based on phase change materials (depends on battery anode and electrolyte chemistry) have been proposed [143].

3. At the *software system* stage, measures of the battery parameters that may be good indicators of safe cell operation, such as cell/pack voltage, temperature, current, and SoC. Estimating low battery capacity and high internal resistance as two main features can increase the probability of a safety issues in those cells. Cell capacity and SoC of each cell inside a module can fluctuate, in spite of being constructed with cells that should be theoretically identical and have experienced the same charge history. Controls at the system software stage therefore allow regularity checks and discovery of abnormal cells [135,144].

Battery behavior related to thermal runaway is a very intricate process involving chemistry, material science, and heat transfer. It should be considered for anode/cathode materials and electrolyte, to cell design [145]. In recent years, finite volume method (FVM) and finite element method (FEM) were used to simulate the temperature distribution of Li-ion battery during regular performance (charging/discharging) based on the thermal models [135,144].

This method was used by Hatchard et al. [146] to simulate the thermal behavior of a lithium ion battery. A one-dimensional model was applied for oven exposure testing. Subsequently, this model was extended to three dimensions by Kim et al. [144]. This model is based on finite volume method to perform three dimensional thermal abuse simulations for Li-ion batteries. The three-dimensional model shows the shapes and volume of cell components and the spatial distributions of temperatures. This model was used to simulate oven tests, and to verify how a local hot spot can spread through the cell. The results demonstrate that smaller cells refuse heat more rapidly than larger cells.

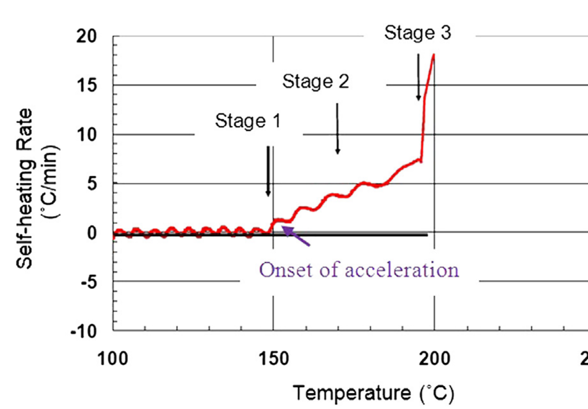


**Fig. 10.** Li-ion heat generation and acceleration of self-heating to diagnose failure in its early stage [141].

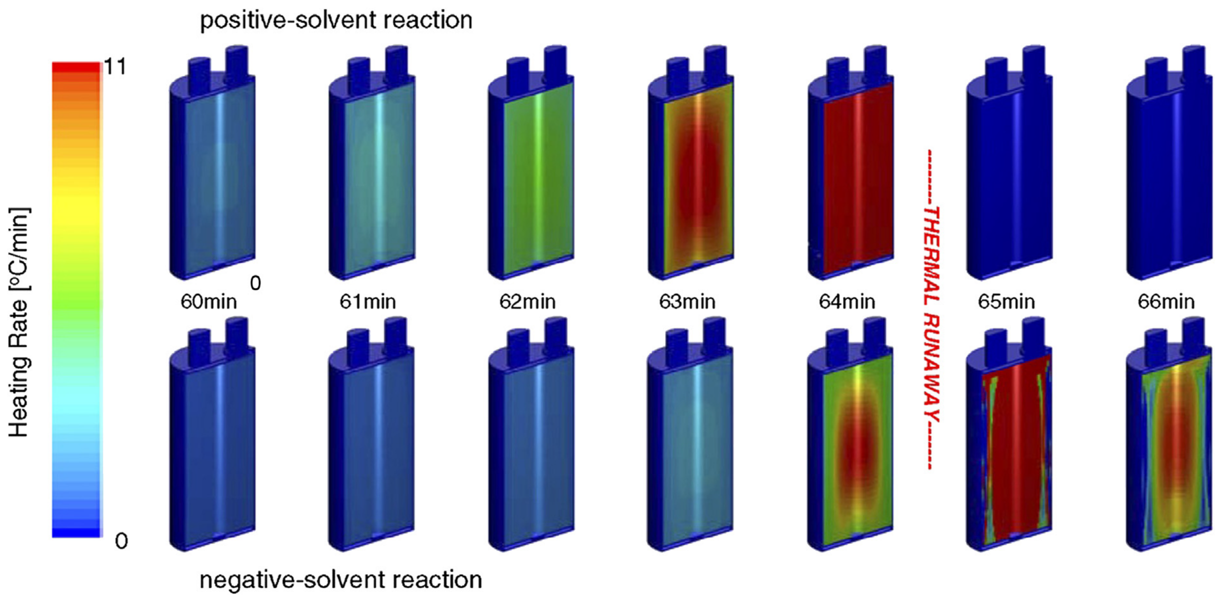


**Fig. 11.** Battery self-heat generation contours in a 155 °C oven test using three-dimensional FVM model, simulated every minute [135,144].

Fig. 11 shows the simulation of three-dimensional model, which illustrates the way in which heat generated inside spreads out in the Azimuthal and longitudinal orders to form a cylindrical shaped sector. The battery entered the thermal runaway at around 64 min in 155 °C oven test conditions.

## 6. Conclusion

This paper reviews and compares various approaches for prognostics and health management of batteries, with a focus on their use in electric vehicles. Three main approaches are employed on battery prognostics physical-model approach, data-driven approach, and fusion model approach. All approaches that are currently used in PHM have certain advantages and drawbacks. The model based approaches take into account the physical processes and failure mechanisms that occur in systems, enabling prognosis of remaining useful life (RUL). A limitation of this approach is that it cannot detect intermittent failures. The data-driven approach is useful when system-specific information is not available. The strength of this approach is diagnostics. The main problem of this approach is that it needs training data to determine RUL, and to establish the thresholds that can be utilized in RUL determination.

The main research issue, therefore, is to find a means to effectively use available battery-specific information; model-based approaches; data-driven diagnostic and prognostic techniques; and prognostics and health management methods. A fusion (or hybrid) approach enables effective use of information from both the model-based and data-driven approaches to achieve dynamic prognosis.

Main challenges in developing an effective prognostics and health management approach for battery systems that need to be addressed include uncertainty in the analysis of mobility, durability and safety during battery life. It is significant to understand and enumerate uncertainty in prediction and estimation from PHM systems for realistic decision-making. Difficulties in uncertainty analysis lie in indicating and enumerating the entire sources that contribute to prediction uncertainties such as measurement noise, model uncertainties, and missing or unavailable training data. Further, it is also necessary to investigate and develop models and data-driven approaches that take into account the critical factors in the operation condition on battery uncertainty. Fig. 12 illustrates the most important parameters for electric vehicle application.

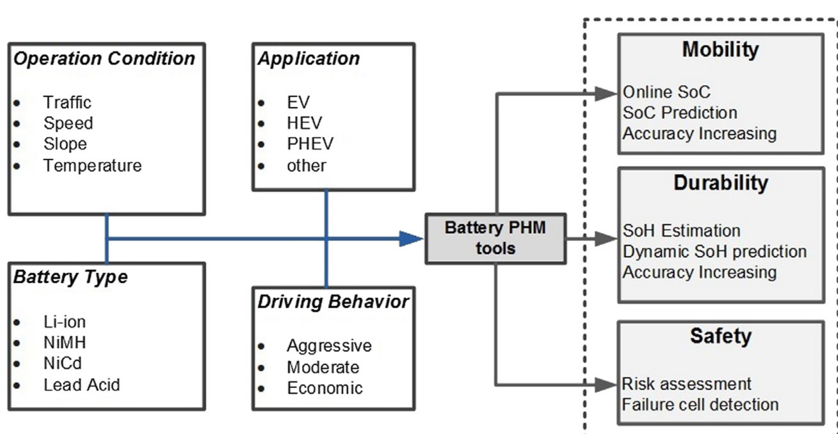


**Fig. 12.** Integration framework of battery PHM.

In order to address the challenges in estimating or predicting battery mobility, durability or safety from physical-model and data-driven approaches, it is necessary to investigate techniques that can define parameters for dynamic conditions. For example, investigating how changes in one or two parameters of the operation condition like road slope can influence EV SoC estimation. Some algorithms have been reviewed in this paper like neuro-fuzzy, extended Kalman filter that can help in this application. Addressing these challenges in research will help build more robust PHM systems that can be implemented for battery systems and vehicles with electric driving modes.

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